Shear strength prediction of RC beams using adaptive neuro-fuzzy inference system

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Received 20 January 2018; received in revised form 23 February 2018; accepted 21 May 2018

KEYWORDS
Adaptive Neuro-Fuzzy Inference System (ANFIS);
Sub-clustering;
Shear strength;
Reinforced concrete beams.

Abstract. In complex engineering problems, there are some inexact conceptions or a lot of parameters that must be considered. Soft computing is an approach that is successfully applied to solve such problems. Determination of fuzzy rules for many problems has not been quite possible by an expert human. In this case, a neuro-fuzzy system that is a combination of neural network (for its ability to learn by datasets) and fuzzy system (for solving the drawback of the neural network) can enhance the performance of the system with several parameters or complex conditions. This paper shows the capability of a neuro-fuzzy system, namely Adaptive Neuro-Fuzzy Inference System (ANFIS), to predict the shear strength of Reinforced Concrete (RC) beams with steel stirrups. For this purpose, the collection of laboratory results published by different works of literature was used to train and test the proposed system. For this purpose, the Sub-Clustering (SC) approach was applied to generate ANFIS. The results indicated that the considered neuro-fuzzy system was able to predict the shear strength of the RC beams, which have been reinforced with steel stirrups.

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1. Introduction

A Reinforced Concrete (RC) beam resists the shear force by several mechanisms such as concrete shear strength (which results from shear compression force and aggregate interlock), vertical reinforcing steel, and shear stirrups. The shear failure of a RC beam is a dangerous brittle failure. Therefore, to prevent this failure, an exact analysis of shear must be considered for the RC element. So far, several experimental research studies have investigated the performance of RC beams to improve the existing relationships presented in common codes such as (ACI 318-14) [1]. In many cases, there is a need for strengthening or retrofitting the RC elements. Moreover, sometimes, there is a need to design the members with high shear strength. To this end, Fibre-Reinforced Polymer (FRP) materials have been widely used for reinforcing or strengthening the structural concrete elements such as RC beams [2,3], especially for shear strengthening. There are several guidelines for determining the shear strength of an RC member with FRP such as ACI 440.1 R-15 [4] and CIDAR [5].

The term of soft computing was first defined by Zadeh (1994) [6]. Wilamowski [7] investigated the advantages of soft computing applied in engineering. There are many applications for this type of computational approach in civil engineering for prediction applications such as load forecasting [8] or earthquake magnitude prediction [9,10]. In structural engineering, the published works on the prediction of the shear capacity of the RC beams with or without material strengthening were divided into two approaches, which are described in the following section. The first one is
based on traditional methods, namely hard computing, and the second one is based on soft computing.

1.1. Prediction based on hard computing

Hard computing as a computational approach is used to solve problems by such traditional means as statistical methods. By considering hard computing, shear strength in RC beams was investigated in the last literature such as size effect on the shear strength of RC beams [11]. Mungwa et al. (1999) developed a flexible shear connector using modern fixing techniques based on an experimental study of composite wood-concrete beam with the aim of higher rigidity, ductility, and ultimate strength [12]. Adhikary et al. (2000) predicted the ultimate shear strength of RC beams with epoxy-bonded continuous horizontal steel plates. According to their results, the continuous steel plates that bonded externally to beam webs were effective in shear strengthening [13]. Finite element methods were also used for the analysis of headed stud shear connectors in the steel-concrete composite beam by Lam and El-Lobody (2001) [14].

According to Maru et al. (2003), whereas differential vertical deflections between adjacent vertical members are small owing to high stiffness of beams, the load transfer between them can be significant [15]. Park et al. (2005) proposed a number of relationships to determine the shear strength of the connection between a steel coupling beam and a RC shear wall in a hybrid wall system [16]. Eun et al. (2006) established the shear strength of a RC deep beam with web opening based on eighteen experimental beams, and showed that the load-carrying capacity of deep beams with openings could be largely improved by an increase in concrete strength [17]. Park and Yun (2006) presented certain equations to predict the strength of steel coupling beam-RC shear wall connections [18]. Park and Yun (2006) also investigated the analytical and experimental studies to develop the strength equations of steel coupling beams-concrete wall connections [19]. Kim and LaFave (2007) studied the most important influencing parameters for joint shear behavior using an extensive database of RC beam-column connection test specimens, exhibiting joint shear failure. They investigated the joint shear cracking stresses and strains by equations and examined the design checks recommended by codes [20]. Ranzi and Zona (2007) presented a model to analyze steel-concrete composite beams with partial shear interaction. The numerical solution was obtained by means of a finite element method, and the numerical results obtained by the proposed model were compared with those of the composite beam model with partial shear interaction in order to determine under which conditions shear deformations of the steel component need to be considered in the analysis and to evaluate how these were affected by the shear connection stiffness [21].

Gara et al. (2009) studied a beam finite element for the long-term analysis of the partial shear interaction at the slab-girder interface using the displacement approach [22]. Jurkiewicz (2009) tested a steel-concrete composite beam, built with a horizontal shear connector under cyclic loading, and showed that the considered connector device allowed satisfactory behavior under static and cyclic loading in accordance with structural modern codes and requirements [23]. BıyıkKaragöz and Arslan (2011) investigated the effect of steel plates with shear studs used in the weak column-strong beam connections based on five RC specimens, which were tested under cyclic loading. The test results indicated that the shear studs improved the strength and stiffness of the specimens [24]. Muhsen and Umemura (2011) proposed a model for estimating the shear strength of RC interior beam-column connections. Their results showed that the estimation of shear strength by the new model was favorable [25]. Ramadass and Thomas (2011) studied the details of the flexure-shear analysis of concrete beams reinforced with GFRP bars. Their prediction indicated that the longitudinally FRP-RC beams with no stirrups failed in shear [26]. Doh et al. (2012) developed a nonlinear layered finite element method with the aim of analyzing the punching shear strength of RC flat plate with spandrel beams [27]. Setiawan and Saptono (2012) investigated the capacity of RC beams with different cross-section types of lateral reinforcement [28]. Shi et al. (2012) analyzed the shear capacity and mechanical properties of deformation comparatively between GFRP-RC beams and steel-RC beams. They also investigated the influencing factors of shear capacity of GFRP-RC beam with circular cross-section, and showed that the influencing coefficient of GFRP on concrete increases with a decrease in the shear span ratio [29].

Gunasekaran et al. (2013) studied the structural shear behavior and shear capacity of the RC beam made with coconut shell and compared their results with the normal control concrete. It was observed that the shear behavior of coconut shell concrete was comparable to that of other lightweight concretes [30]. Houachine et al. (2013) proposed an analytical method, and showed that interfacial shear stresses and pull forces were suitably approximated by using the high-order function of shear deformation [31]. Sung et al. (2013) presented a nonlinear pushover analysis procedure that considers shear failure at beam-column joints, which can be used to estimate the structural behavior of RC frames [32]. Bui et al. (2014) proposed a stress-resultant model that combines the descriptions of the diffuse plastic failure in the beam and the localized failure with the creation of the corresponding plastic
hinges, representing both bending and shear failure mechanisms [33]. Long et al. (2014) investigated those models for simulating beam-column members with a wide range of shear span-to-depth ratios and, also, proposed a method by comparing numerical predictions with experimental results [34].

Mancer et al. (2014) studied validation of a numerical model that could approximate the shear behavior of RC rectangular beams strengthened against shear with externally applied open hoop FRP strips [35]. Yu et al. (2014) tested five pre-stressed steel ultra-high-strength RC beams monotonically until shear failure to study the failure pattern, load-deflection behavior, shear capacity, shear crack width, and shear ductility [36]. Alam et al. (2015) developed Kenaf Fibre-Reinforced Polymer (KFRP) laminate for shear strengthening of RC beams and proposed designs and theoretical models [37]. Bampi and Elghazouli (2015) examined the shear transfer mechanisms and ultimate behavior of hybrid systems consisting of RC beams connected to structural steel columns [38]. Shahbazpanahi et al. (2015) developed a numerical method for modeling shear-strengthening of the RC beam by FRP composites, and observed that the load capacity increased with the number of CFRP sheets in the shear span [39]. Campione et al. (2015) presented a calculation method to predict the shear resistance of precast composite beams and developed their model on the basis of the results of a referenced experimental campaign of three-point bending tests [40]. Lu et al. (2015) proposed a joint connecting beam, which is a widely used technology of the mechanic sleeve and sleeve-mortar splicing connections to connect the reinforcement of precast concrete shear walls [41]. Zhang et al. (2015) studied a mechanics-based segmental approach to analyze an RC beam with any type of concrete and reinforcement based on a segmental approach and, also, proposed a simplified closed-form solution for design [42].

1.2. Prediction based on soft computing

Soft computing is an approach that can be realized by experimental or analytical suitable data rather than hard computing. This computational method is used to solve problems with uncertain or complex conditions in multi-dimensional space. It has high accuracy. In concrete structures, there are more parameters that affect analysis or design, and recent studies have indicated that soft computing has been able to function well in structural engineering applications such as the shear strength of RC beams.

Adhikary and Mutsumoshi (2004) investigated the ability of the multilayer feedforward artificial neural network to predict the ultimate shear capacity of RC beams with web-bonded steel plates; they showed that Artificial Neural Network (ANN) predicted the ultimate shear capacity of RC beams and cross-validated the results of other models such as a finite element model and analytically empirical models [43]. Adhikary and Mutsumoshi (2006) predicted the ultimate shear strength of steel fibre RC beams based on a multilayer feed forward neural network with the back propagation learning algorithm. They showed that ANN was able to consider various predictions [44]. The shear resistance of RC beams using neural networks was estimated by Abdalla et al. (2007). This study confirmed that ANN could be used for prediction purposes [45]. Nehdi et al. (2007) used Zcutty equation [46] to optimize the equations of calculating the shear capacity of FRP-RC beams with and without shear reinforcement based on the genetic algorithm [47].

Ahn et al. (2007) investigated the shear force characteristics of steel fiber-RC with varying shapes and mixture ratios using artificial neural networks with backpropagation algorithm, and showed that ANN was a suitable approach to prediction [48]. Perera et al. (2010) applied neural networks to predict the ultimate shear strength of FRP-strengthened RC beams by a database that includes shear strengthened RC beams with FRP using U-jacketing and full wrapping configurations. They also presented design equations to calculate the shear capacity of FRP-strengthened RC beams in shear [49]. Tanarslan (2011) investigated the performance of ANN in predicting the shear capacity of the RC beams retrofitted in shear by means of side-bonded FRP; obtained results demonstrated the higher accuracy of those values obtained by ANN [50]. Tanarslan et al. (2012) used the back propagation network to determine the shear strength contribution of RC beams strengthened in shear by retrofitting externally bonded wrapped and U-jacketed FRP reinforcement, and showed that ANN was a good tool for predicting [51]. Lee and Lee (2014) studied the application of a theoretical approach to predict the shear strength of slender FRP-RC flexural members without stirrups [52]. Nasrolahzadeh and basiri (2014) presented a fuzzy system with Gaussian membership functions and the Takagi-Sugeno inference system using the subtractive clustering algorithm to predict the shear strength of FRP-RC beams. Their fuzzy system was able to predict the shear strength of FRP-RC beams [53]. Perera et al. (2014) proposed formulations of design equations for RC beams shear strengthened with Near Surface Mounted (NSM) FRP rods using artificial neural networks, created by backpropagation and the training algorithm of Levenberg-Marquardt, to predict the capacity of the shear strengthened RC beams with NSM-FRP; their results indicated that the ANN could be used for evaluating the shear capacity of RC members strengthened with NSM-FRP [54]. A shear design approach to predicting the contribution of the anchorage FRP reinforcement to the ultimate shear capacity using feed-forward back-
propagation algorithm was also proposed by Tanarslan et al. (2015) [55]. Furthermore, there are some other investigations based on soft computing methods for estimating the response of concrete structures [56–70].

1.3. The aim of the study
Failure under shear of a reinforced beam with longitudinal bars and stirrups in the web may occur by diagonal tension, which is resisted by beam action in the shear span without web reinforcement and also truss mechanism of web reinforcement, generating an additional resisting mechanism to shear for the beam [71].

The shear resistance in a usual RC beam is governed by shear strength of the compression zone (which depends on concrete strength), aggregate interlock, dowel effect of tensile longitudinal bars, and shear reinforcements such as stirrups. Shear forces produce shear stresses [72], and high shear stress generally causes cracks in RC beams. The failure in shear for a RC beam is a mode of failure due to its brittleness. Because of the importance of this failure, it is necessary to consider more investigations, and the current study follows this purpose based on neuro-fuzzy system as a soft computing approach, which has not been applied before.

2. Adaptive ANFIS
2.1. Structure of ANFIS
ANFIS is a fuzzy inference system for a function approximation problem based on hybrid neuro-fuzzy systems, as introduced by Jang [73]. ANFIS uses a Sugeno-type fuzzy system in a five-layer network (the input layer not counted by Jang) for two inputs \( x \) and \( y \) and one output \( z \), as illustrated in Figure 1.

Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno’s types:

- Rule 1: If \( x \) is \( A_1 \) and \( y \) is \( B_1 \), then \( f_1 = p_1 x + q_1 y + r_1 \);

- Rule 2: If \( x \) is \( A_2 \) and \( y \) is \( B_2 \), then \( f_2 = p_2 x + q_2 y + r_2 \).

Then, the corresponding equivalent ANFIS architecture is shown in Figure 1.

The node functions in the same layer are of the same function family as described below [74].

Layer 1: Every node \( i \) in this layer is a square node with a node function as Eq. (1):

\[
O^1_i = \mu_{A_i}(x),
\]

(1)

where \( x \) is the input to node \( i \), and \( A_i \) is the linguistic label (such as “small” or “large”) associated with this node function. In other words, \( O^1_i \) is the membership function of \( A_i \), and it specifies the degree to which the given \( x \) satisfies the quantifier \( A_i \). Any continuous and piece-wise differentiable functions, such as commonly used bell-shaped, trapezoidal, or triangular-shaped membership functions, are qualified candidates for node function in this layer.

Layer 2: Every node in this layer is a circle node labeled II that multiples the incoming signals and sends the product out. For instance:

\[
w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1, 2.
\]

(2)

Each node output represents the T-norm operators that combine the possible input membership grades in order to compute the firing strength of a rule.

Layer 3: Every node in this layer is a circle node labeled N. The \( i \)th node calculates the ratio of the \( i \)th rule’s firing strength to the sum of all rules’ firing strengths:

\[
\tilde{\omega}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2.
\]

(3)

For convenience, outputs of this layer will be called normalized firing strengths.

![Figure 1](image-url)  
*Figure 1.* Structure of Adaptive Neuro-Fuzzy Inference System (ANFIS) with 2 inputs and 2 rules. A square node (adaptive node) has parameters, while a circle node (fixed node) has none [24].
Layer 4: Every node $i$ in this layer is a square node with a node function:

$$O_i^4 = \tilde{a}_i f_i = \tilde{a}_i (p_i x + q_i y + r_i),$$  \hfill (4)

where $\tilde{a}_i$ is the output of Layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as consequent parameters that are adjustable.

Layer 5: The single node in this layer is a circle node (adaptive node) labeled as $\Sigma$ that computes the overall output as a summation of all incoming signals:

$$O_i^5 = \text{overall output} = \Sigma_i \tilde{a}_i f_i = \frac{\sum_i \tilde{a}_i f_i}{\sum_i \tilde{a}_i^2}.$$ \hfill (5)

2.2. Sub-Clustering (SC) approach

Clustering is a task of assigning a set of data to groups called clusters to discover structures and patterns in a dataset, and the radius of a cluster is the maximum distance between all the points and the centroid. Sub-Clustering (SC) is based on classifying each point of the dataset just to one cluster and was proposed by Chin [75]. The SC method assumes that each data point is a potential cluster center and calculates the potential for each data point based on the density of surrounding data points [9]. The measure of the potential for a data point is a function of its distances to all other data points. A data point with many neighboring data points will have a high potential value. The data point with the highest potential is selected as the first cluster center, and the potential of data points near the first cluster center is destroyed. Then, data points with the highest remaining potential as the next cluster center and the potential of data points near the new cluster center are destroyed [9]. It is notable that the influence radius of the cluster is critical for determining the number of clusters, and the data points outside this radius have insignificant influence on the potential. In addition, a smaller radius leads to many smaller clusters in the data space, resulting in more rules [75].

3. Database

ANFIS requires a dataset for training. It is mentioned that the ability of a system such as ANN or ANFIS depends on the data used in training or validation phase. In this paper, the collection of 194 experimental results, published in the literature, was applied to train and test the ANFIS [76-93]. A summary of the dataset is presented in Table 1. The parameters in this table include width of the member ($b$), effective depth of the member ($d$), concrete compressive strength ($f_{cc}$), the yielding strength of transverse reinforcement ($f_{ty}$), the yield strength of longitudinal reinforcement ($f_{ty}$), web cross-sectional area of the reinforcement as a proportion of the cross-sectional area of the beam ($\rho_{ct}$), the transverse reinforcement ratio ($\rho_{ct}$), and the experimental shear strength ($V$).

To classify the interval of values that are different on the same scale, a normalizing procedure was used. A simple normalization relationship within a value of 0.1 to 0.9, which is used for normalization in this paper, is Eq. (6):

$$x_i = \frac{0.8}{x_{\text{max}} - x_{\text{min}}} x_i + 0.1,$$ \hfill (6)

where $x_i$ is the normalized value of a certain parameter, $x$ is the measured value for this parameter, and $x_{\text{min}}$ and $x_{\text{max}}$ are the minimum and maximum values in the database for this parameter, respectively.

In order to use the proposed ANFIS in this paper and in accordance with Eq. (6), the minimum and maximum values of each variable are required to calculate its normal value (0.1 to 0.9 in this paper). These amounts can be extracted from Table 1 and used in the determination process of the ANFIS. The other details such as mean or average were also presented to gain knowledge of the applied database.

4. The proposed ANFIS model

4.1. Properties of the model

First, the datasets are divided into training data, consisting of 160 pairs of inputs and outputs, and test

<table>
<thead>
<tr>
<th>Mean</th>
<th>Average</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b$ (mm)</td>
<td>203.00</td>
<td>207.40</td>
<td>76.00</td>
<td>457.00</td>
</tr>
<tr>
<td>$d$ (mm)</td>
<td>383.00</td>
<td>358.88</td>
<td>95.00</td>
<td>851.00</td>
</tr>
<tr>
<td>$f_{cc}$ (MPa)</td>
<td>28.00</td>
<td>29.60</td>
<td>12.80</td>
<td>30.30</td>
</tr>
<tr>
<td>$f_{ty}$ (MPa)</td>
<td>331.00</td>
<td>384.09</td>
<td>159.00</td>
<td>820.00</td>
</tr>
<tr>
<td>$f_{ty}$ (MPa)</td>
<td>434.00</td>
<td>459.80</td>
<td>300.00</td>
<td>707.00</td>
</tr>
<tr>
<td>$\rho_{ct}$</td>
<td>2.70</td>
<td>2.72</td>
<td>1.00</td>
<td>4.80</td>
</tr>
<tr>
<td>$\rho_{ct}$</td>
<td>0.30</td>
<td>0.36</td>
<td>0.10</td>
<td>1.90</td>
</tr>
<tr>
<td>$V$ (kN)</td>
<td>214.00</td>
<td>252.96</td>
<td>13.60</td>
<td>836.10</td>
</tr>
</tbody>
</table>
data with 34 pairs. In this study, ANFIS with seven parameters includes width of the member, effective depth of the member, concrete compressive strength, the yielding strength of transverse reinforcement, the yielding strength of longitudinal reinforcement, web cross-sectional area of the reinforcement as a proportion of the cross-sectional area of the beam, and also the transverse reinforcement ratio used for predicting the shear strength of RC beams with steel stirrups. The range of influence was considered as 0.6 (to specify a cluster center’ range of influence in each data dimension) and the squash factor (the factor to multiply the range of influence that determines the neighborhood of a cluster) as 1.25. The acceptance ratio (the factor that sets the potential as a fraction of the potential of the first cluster center, above which another data point is accepted as a cluster center) and rejection ratio (the factor that sets the potential as a fraction of the potential of the first cluster center, below which another data point is accepted as a cluster center) were 0.5 and 0.15, respectively.

4.2. Membership functions and clusters
ANFIS based on SC approach used a Gaussian membership function (Figure 2) for input parameters, shown in Figures 3-9, as follows:

\[ \mu(x; \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}}, \]

where \( c \) is the mean and \( \sigma \) is the variance for \( x \).

It is mentioned that two parameters including \( \sigma \) and \( c \) are required to define this type of membership function. For each input, six Gaussian membership functions were used, whose details are presented in Table 2. The parameters of clusters (CL) are also shown in Table 3. These parameters consider the output’s equations (Eq. (8)) that are used to calculate the shear strength based on Eq. (4). The final ANFIS structure is illustrated in Figure 10.

\[ CL_j = a_1x_1 + a_2x_2 + a_3x_3 + C, \quad j = 1, \ldots, 6. \] (8)

The parameters \( a_1, \ldots, a_7 \) are coefficients of the input \( x_1, \ldots, x_7 \). Parameter \( C \) deals with a constant value. The amounts of these parameters are presented in Table 3.
4.3. Rules
In this study, first, several ANFIS models with different approaches and parameters were created; finally, the best of them were considered. The selected model generated based on the subtractive clustering method used six simple rules including:

Rule 1: If “v” is C1 and “d” is C1 and “feco” is C1 and “prt” is C1 and “fry” is C1 and “psl” is C1 and “fys” is C1, then “V” is in Cluster 1;

Rule 2: If “v” is C2 and “d” is C2 and “feco” is C2 and “prt” is C2 and “fry” is C2 and “psl” is C2 and “fys” is C2, then “V” is in Cluster 2;

Rule 3: If “v” is C3 and “d” is C3 and “feco” is C3 and “prt” is C3 and “fry” is C3 and “psl” is C3 and “fys” is C3, then “V” is in Cluster 3;

Rule 4: If “v” is C4 and “d” is C4 and “feco” is C4 and “prt” is C4 and “fry” is C4 and “psl” is C4 and “fys” is C4, then “V” is in Cluster 4;

Rule 5: If “v” is C5 and “d” is C5 and “feco” is C5 and “prt” is C5 and “fry” is C5 and “psl” is C5 and “fys” is C5, then “V” is in Cluster 5;

Rule 6: If “v” is C6 and “d” is C6 and “feco” is C6 and “prt” is C6 and “fry” is C6 and “psl” is C6 and “fys” is C6, then “V” is in Cluster 6.

4.4. Final ANFIS output
Based on the rule base presented in the previous section, the rule’s weight W for each of the six rules can be calculated as follows:

\[
W_1 = (C1_1) \times (C1_2) \times (C1_3) \times (C1_4) \\
\times (C1_5) \times (C1_6)
\]

\[
W_2 = (C2_1) \times (C2_2) \times (C2_3) \times (C2_4) \\
\times (C2_5) \times (C2_6)
\]

\[
W_3 = (C3_1) \times (C3_2) \times (C3_3) \times (C3_4) \\
\times (C3_5) \times (C3_6)
\]

\[
W_4 = (C4_1) \times (C4_2) \times (C4_3) \times (C4_4) \\
\times (C4_5) \times (C4_6)
\]

\[
W_5 = (C5_1) \times (C5_2) \times (C5_3) \times (C5_4) \\
\times (C5_5) \times (C5_6)
\]
Table 2. Parameters of the membership functions for each of the inputs.

<table>
<thead>
<tr>
<th>Input</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>C6</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b$ (mm)</td>
<td>0.21</td>
<td>0.38</td>
<td>0.14</td>
<td>0.57</td>
<td>0.15</td>
<td>0.36</td>
</tr>
<tr>
<td>$d$ (mm)</td>
<td>0.21</td>
<td>0.40</td>
<td>0.12</td>
<td>0.49</td>
<td>0.12</td>
<td>0.45</td>
</tr>
<tr>
<td>$f_{\text{ceo}}$ (MPa)</td>
<td>0.17</td>
<td>0.37</td>
<td>0.17</td>
<td>0.40</td>
<td>0.16</td>
<td>0.37</td>
</tr>
<tr>
<td>$\rho_{\text{et}}$</td>
<td>0.19</td>
<td>0.55</td>
<td>0.16</td>
<td>0.32</td>
<td>0.20</td>
<td>0.25</td>
</tr>
<tr>
<td>$f_{\text{st}}$</td>
<td>0.15</td>
<td>0.15</td>
<td>0.20</td>
<td>0.79</td>
<td>0.15</td>
<td>0.13</td>
</tr>
<tr>
<td>$\rho_{\text{st}}$</td>
<td>0.18</td>
<td>0.22</td>
<td>0.15</td>
<td>0.10</td>
<td>0.21</td>
<td>0.26</td>
</tr>
<tr>
<td>$f_{\text{sy}}$</td>
<td>0.17</td>
<td>0.34</td>
<td>0.20</td>
<td>0.33</td>
<td>0.17</td>
<td>0.29</td>
</tr>
</tbody>
</table>

Table 3. Parameters of the output’s clusters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Clusters (CL)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{1}$: Coefficient of $b$</td>
<td>Clusters (CL)</td>
</tr>
<tr>
<td>$a_{2}$: Coefficient of $d$</td>
<td>Clusters (CL)</td>
</tr>
<tr>
<td>$a_{3}$: Coefficient of $f_{\text{ceo}}$</td>
<td>Clusters (CL)</td>
</tr>
<tr>
<td>$a_{4}$: Coefficient of $\rho_{\text{et}}$</td>
<td>Clusters (CL)</td>
</tr>
<tr>
<td>$a_{5}$: Coefficient of $f_{\text{st}}$</td>
<td>Clusters (CL)</td>
</tr>
<tr>
<td>$a_{6}$: Coefficient of $\rho_{\text{st}}$</td>
<td>Clusters (CL)</td>
</tr>
<tr>
<td>$a_{7}$: Coefficient of $f_{\text{sy}}$</td>
<td>Clusters (CL)</td>
</tr>
<tr>
<td>$c$: Coefficient of constant</td>
<td>Clusters (CL)</td>
</tr>
</tbody>
</table>

\[ W_{o} = (CGX_{1}) \times (CGX_{2}) \times (CGX_{3}) \times (CGX_{4}) \times (CGX_{5}) \times (CGX_{6}). \]

The normal value of the shear strength ($V_n$) based on the ANFIS model can be determined by Eq. (9). It is worth noting that the output of Eq. (9) can be easily converted to the real value based on Eq. (6) and the amount values of Table 1 (the minimum and maximum of the output parameter).

\[
V_n = \frac{\sum_{j=1}^{6} w_{\text{Rule,}_j} C L_{j}}{\sum_{j=1}^{6} w_{\text{Rule,}_j}}. \tag{9}
\]

5. Results

5.1. ANFIS results

After generating ANFIS, it was trained with considered 160 pairs of inputs-output based on selected conditions, as presented in previous sections. Figure 11 shows the training process, indicating that the ANFIS reached its minimum error at less than 50 epochs. The outputs of the ANFIS against experimental data (normalized values between 0.1 to 0.9) are presented in Figure 12. Based on the figure, ANFIS has a good performance in the training phase. The selected neuro-fuzzy also predicted the shear strength of RC beams with steel stirrups, too (Figure 13).

![Figure 11. The training process.](image)

![Figure 12. The training results of Adaptive Neuro-Fuzzy Inference System (ANFIS).](image)

The proposed ANFIS in this paper has a correlation coefficient ($R^2$) equal to 0.98 and 0.94 in training and test phases, respectively. These values are clearly shown in Figures 14 and 15. It is important that the selected data for training cover all of the ranges of shear...
Table 4. Distribution of error for the proposed Adaptive Neuro-Fuzzy Inference System (ANFIS) based on experimental data.

<table>
<thead>
<tr>
<th>Range of error (%)</th>
<th>Number of data in the range of ANFIS</th>
<th>Percentage of whole data for ANFIS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Train data</td>
<td>Test data</td>
</tr>
<tr>
<td>&lt; ±5</td>
<td>65</td>
<td>12</td>
</tr>
<tr>
<td>&lt; ±10</td>
<td>112</td>
<td>22</td>
</tr>
<tr>
<td>&lt; ±15</td>
<td>133</td>
<td>26</td>
</tr>
<tr>
<td>&lt; ±20</td>
<td>143</td>
<td>27</td>
</tr>
<tr>
<td>&lt; ±25</td>
<td>153</td>
<td>28</td>
</tr>
<tr>
<td>&lt; ±30</td>
<td>156</td>
<td>28</td>
</tr>
<tr>
<td>&lt; ±35</td>
<td>157</td>
<td>29</td>
</tr>
<tr>
<td>&lt; ±40</td>
<td>158</td>
<td>30</td>
</tr>
<tr>
<td>&lt; ±45</td>
<td>160</td>
<td>31</td>
</tr>
<tr>
<td>&gt; ±45</td>
<td>0</td>
<td>3</td>
</tr>
</tbody>
</table>

Figure 13. The test results of Adaptive Neuro-Fuzzy Inference System (ANFIS).

Figure 14. The results of Adaptive Neuro-Fuzzy Inference System (ANFIS) for the training phase.

Figure 15. The results of Adaptive Neuro-Fuzzy Inference System (ANFIS) for test data.

values. This is due to an increase in the accuracy of the ANFIS.

5.2. Error calculations and correlation coefficient values
The details of results of the ANFIS have included one point in the training (0.007) and two points in the test (0.074, 0.076), having values less than 0.1. These amounts lead to negative values after converting them to real values (based on Eq. (6)). To avoid this, it is assumed that they correspond with 0.1. Because these amounts are so close to 0.1, the considered assumption can be suitable. Table 4 presents the final results after converting them to the whole 160 training data and 34 test data. A comparison between the results of the proposed ANFIS and other codes for $\frac{f_{\text{ANFIS}}}{f_{\text{label}}}$ ratio showed a value equal to 0.908 for ANFIS, while it is equal to 1.88, 1.48, 1.37 for ACI 318-08, CSA A23.3-04, and CEN 2004, respectively.

6. Conclusion
In this paper, a neuro-fuzzy system called Adaptive Neuro-Fuzzy Inference System (ANFIS) was proposed to predict the shear strength of Reinforced Concrete (RC) beams with steel stirrups using seven parameters including the width of the member, effective depth of the member, concrete compressive strength, the yielding strength of transverse reinforcement, the yielding strength of longitudinal reinforcement, web cross-sectional area of the reinforcement as a proportion of the cross-sectional area of the beam, and also the
transverse reinforcement ratio. ANFIS requires a
database to determine its value. It was mentioned
that a collection of more data could directly affect
the results of ANFIS and lead to a model with high
accuracy. In this paper, ANFIS was generated by
the subtractive clustering method and trained with
160 data, as collected from the literature based on
experimental data. Afterward, the neuro-fuzzy model
was examined to specify the capability of ANFIS; for
this purpose, 34 data were considered. The final results
indicated that ANFIS could be used to predict the
shear strength of RC beams with suitable accuracy.
ANFIS is a powerful tool for determining the values of
parameters in multi-dimensional space with uncertain
conditions. As a result, there are many types of
research in civil engineering that have been done, and
the current paper presented another application of this
neuro-fuzzy system.

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